Analysis of Total Factor Productivity of China's Manufacturing Industry based on DEA Model

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Abstract: Based on the data of capital, labor input and output value of China's manufacturing industry released by the National Bureau of statistics, this paper analyzes the total factor productivity of 31 manufacturing industry segments in China from 2012 to 2016 by using the input-oriented CCR model in DEA model. The results show that the total factor productivity of China's manufacturing industry is mainly affected by technical efficiency. After a series of data processing, it is found that China's manufacturing industry has not yet entered the stage of high-quality development, and there are still some problems such as low technology level, high resource dependence and low degree of automation. Finally, this paper puts forward targeted policy recommendations for the realization of high-quality development of China's manufacturing industry.

1. Introduction

Manufacturing productivity is not only an important factor to measure a country's productivity level, but also an important indicator to distinguish developed countries from developing countries. The report on the development index of China's manufacturing power in 2019 released at the fifth forum of China's manufacturing powers points out from the perspective of international comparison that the development scale of China's manufacturing industry ranks first in the world, but the indicators of quality benefit, structural optimization and sustainable development are far from those of developed countries, especially the United States, Germany and Japan. The premise of narrowing the gap is to clarify its own development situation. Therefore, this paper will use DEA model to calculate and analyze the total factor productivity of China's manufacturing industry from the perspective of input-output analysis.[1]

The existing analysis of total factor productivity of manufacturing industry is mostly limited to a province or a region: Zhao man et al. (2020) used DEA Malmquist model to evaluate the total factor productivity of manufacturing industry in Jiangsu Province from three dimensions of time, industry segmentation and R & D intensity; Jiang Jiyu used non parametric DEA Malmquist index method to analyze the total factor productivity of manufacturing industry in Anhui Province Liu Xiao (2019) also used Malmquist DEA method to compare the production efficiency of manufacturing industry in Beijing Tianjin Hebei and Yangtze River Delta from the growth rate of technological progress, the growth rate of technical efficiency and total factor productivity.[2][3][4]

It is worth noting that although the existing researches on TFP of manufacturing industry adopt the same research methods, the classification and index selection of DEA model in the dimensions of input-output orientation and scale efficiency are not the same. Therefore, this paper will combine the characteristics of China's manufacturing industry and select the model and index suitable for the measurement of TFP.

2. Selection of DEA model

2.1 Model interpretation

Referring to the analysis framework of Chen Jiawei's (2017) research on housing market information search efficiency and combining with the characteristics of manufacturing industry, this

paper assumes that the manufacturing industry contains n sub industries, namely n DMU, which are recorded as DMU j (J = 1,2,... N), and each DMU corresponds to M elements input and Q output, which are respectively recorded as x_i (I = 1,2,... M), y_r (r = 1,2,... Q).The weights of input and output are v_i (I = 1,2,..., m) and u_r (r = 1,2,... Q), respectively. Let the input-output ratio of DMU_k be h_k,

$$h_k = \frac{u_1 y_{1k} + u_2 y_{2k} + ... + u_q y_{qk}}{v_1 x_{1k} + v_2 x_{2k} + ... + v_m x_{mk}} = \frac{\sum_{r=1}^{q} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} (v \geq 0; u \geq 0)^{[5]}$$

The additional condition of the model is that the efficiency value θ calculated by DMU of all manufacturing industries using the above weights is distributed in the interval [0,1]. $\dfrac{\sum_{r=1}^{q} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1$

Based on the above conditions, the CCR model can be established as follows:

$$\max \frac{\sum_{r=1}^{q} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

$$s.t. \frac{\sum_{r=1}^{q} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1 (u \geq 0; v \geq 0; i = 1,2,...m; r = 1,2,...,q; j = 1,2,...n)$$

(1)

The linear programming shows that the weights u and V determined by the model can maximize the efficiency of DMU when the efficiency values of all manufacturing industries are less than or equal to 1.It is not difficult to understand that when the input is changed to the original t times, the output will change by the same multiple in the same direction.

$$\max \frac{\sum_{r=1}^{q} u_r t y_{rk}}{\sum_{i=1}^{m} v_i t x_{ik}} = \frac{t \sum_{r=1}^{q} u_r y_{rk}}{t \sum_{i=1}^{m} v_i x_{ik}} = \frac{\sum_{r=1}^{q} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

(2)

Through equivalent change, then u = Tu, v = TV, the nonlinear model (1) can be changed into an equivalent linear programming model

$$\max \sum_{r=1}^{q} u_r y_{rk}$$

$$s.t. \sum_{r=1}^{q} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1 (u \geq 0; v \geq 0; i = 1,2,..., m; r = 1,2,...,q; j = 1,2,...,n)$$

(3)

The dual model of model (3) is

$$\min \theta$$

$$s.t. \sum_{i=1}^{m} \lambda_j x_{ij} \leq \theta x_{ik}$$

$$\sum_{i=1}^{m} \lambda_j y_{rj} \geq y_{rk} \quad (\lambda \geq 0; i = 1, 2, \ldots, m; r = 1, 2, \ldots, q; j = 1, 2, \ldots, n)$$

(4)

Where λ is the linear combination coefficient of manufacturing industry DMU, and the optimal solution θ of the linear programming is the efficiency value of industry DMU, and θ * belongs to [0,1].Obviously, the input of the DMU is not greater than that of the DMU_k, and the output is not less than that of the DMU_k ,If DMU_k is in the state of invalid rate, the virtual DMU constructed by using

the optimal solution represents the evaluation target value of DMU($\hat{x} = \sum_{j=1}^{m} \lambda_j^* x_j$, $\hat{y} = \sum_{j=1}^{n} \lambda_j^* y_j$).

The above model is recorded as the input oriented CCR model.

3. Data selection

In this paper, DEAP2.1 is used as data processing tool to decompose TFPCH of manufacturing industry into four parts

$$TFPCH = EFFCH \times SECH = TECHCH \times PECH \times SECH$$

Table 1 Total Factor Productivity and its decomposition of China's manufacturing industry from 2012 to 2016

particular year	EFFCH	TECHCH	PECH	SECH	TFPCH
2012~2013	1.016	1.005	1.000	1.016	1.022
2013~2014	0.972	1.069	0.968	1.003	1.039
2014~2015	1.045	0.946	1.044	1.001	0.988
2015~2016	0.908	1.114	0.904	1.005	1.011
mean	0.984	1.032	0.978	1.006	1.015

4. Result analysis

The total factor productivity of China's manufacturing industry is on the rise, with an average growth rate of 1.5% in the past five years, of which the growth rate of scale efficiency is only 0.6%, and the fluctuation is relatively gentle. In the five years, the two increases of total factor productivity in 2013-2014 and 2015-2016 are mainly related to technological progress, which shows that technological progress can effectively drive the rise of total factor productivity of manufacturing industry.

Although the average growth rate of technological progress in the past five years is 3.2%, the average growth rate of comprehensive technical efficiency is - 1.6%, showing a slight retrogression. The main reason is the stagnation of pure technical efficiency growth, that is, the low production efficiency caused by backward management and technology level of manufacturing enterprises, which seriously hindered the technological progress and transformation and upgrading of China's manufacturing industry. After adding the trend of GDP deflator, we can see that although the total factor productivity of China's manufacturing industry has increased slightly, technological progress has not brought about the improvement of economic development level. On the contrary, the overall technical level of manufacturing industry is still backward, and the low efficiency of resource management and allocation, to a certain extent, has led to the decline of GDP deflator index year by year. Therefore, in order to avoid the waste of resources in China's manufacturing industry, it is necessary to improve the efficiency of resource allocation and technology innovation.
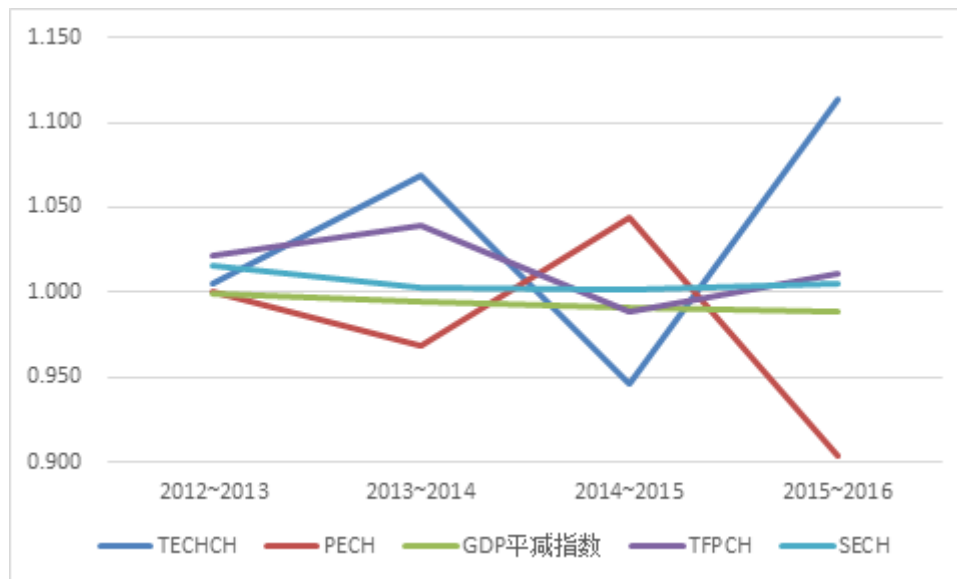
Figure 1: Trend of GDP deflator and total factor productivity

5. Conclusions and policy recommendations

5.1 Conclusion

At present, China's manufacturing industry is in the stage of rapid technological progress, but the overall technical efficiency is low, and there is still a lot of room for development in the future.

At present, China's manufacturing industry is still highly dependent on natural resources and labor

(1) The growth of total factor productivity of manufacturing industry mainly depends on the support of resource consuming industries;

(2) The degree of automation and intelligence of light industry manufacturing industry is low, and the production efficiency is low;

Finally, the manufacturing industry is divided into high-tech, high-tech and low-tech industries. It is found that the high-tech manufacturing industry is actively exploring the path of high-quality development, but the development of low-tech manufacturing industry is sluggish and even backward, which reflects the uneven distribution of capital and high-quality talents among different industries.

5.2 Policy recommendations

Combined with the analysis conclusion of this paper, the following suggestions are put forward for the realization of high-quality development of China's manufacturing industry[6]

(1) Improve the income level and quality of life of residents, stimulate consumer consumption, stimulate consumer demand for high-quality products, force low-efficiency manufacturers to transform and upgrade through the role of market supply and demand, and improve production efficiency and product quality;

(2) Promote the combination of Internet, big data, artificial intelligence and other new generation information technology with traditional manufacturing industry, and improve the industrial structure. The new manufacturing industry cluster and industrial chain based on new technology can improve the efficiency of capital turnover and resource allocation, thus creating the possibility for the improvement of scale efficiency;

(3) It emphasizes sustainable development and vigorously develops green economy such as new energy to reduce dependence on natural resources and damage to environment;

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